The Effects of Industrialization and Economic Growth on Sustainable Development Decoupling in China

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ABSTRACT

With the development of industrialization, the problem of mutual economic and environmental constraints has increasingly prominent. The purpose of this study is to inspect China's decoupling index and ultimately promote the sustainable development decoupling in China. This paper focuses on the Tapio decoupling model and the panel-ARDL model to examine the impact of decoupling 30 Chinese provinces in 2005-2019. The results found that (1) Economic growth, industrialization, and carbon intensity have a catalytic role in promoting the decoupling states, while energy consumption structure and consumer price index have a suppressive influence. (2) At present, most Chinese provinces are in a weak decoupling state, and CO2 emissions are most serious from eastern China to western China. The policies are also given from the perspective of sustainable development, such as improving energy utilization, encouraging investment in energy conversion sectors, and establishing a corresponding low-carbon reward and punishment system.

Keywords: Carbon Decoupling; Economic Growth; Industrialization; Sustainable Development.

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1. INTRODUCTION

With the increasingly obvious impact of industrialization on China's economic growth (EG), the rapid EG has also brought many environmental problems. These issues brought serious resource consumption and environmental pollution to China, of which air pollution caused by carbon emissions (CE) is one of the topmost serious problems. Many countries in the world have achieved economic advantages through the industrial revolution, but they luxuriously waste resources. And with the rapid deterioration in environmental problems, the damage to CE has increased. As we all know, a few emissions from China are equivalent to a bigger air pollution in the world, which also means that China has a great responsibility to alleviate the carbon pollution burden.

Based on the above situation, China will try to increase its contribution to the global climate targets and meet its environmental goals. In 2015, China also participated to join the Paris Climate Conference and claimed that China will devote more attention to

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decreasing 60%-65% of its carbon intensity from 2005 by 2030. Moreover, with industrial and technological advances, the Chinese economy is making steady progress. Similar to the GDP growth rate of 8.1% and 18% of the global economy in 2021 (China National Statistical Yearbook). China also a necessary economy worldwide and still coordinates economic growth with its environmental issues related to industrialization.

Unfortunately, there are still many developmental barriers. On the one hand, the typical industrial problems of China are as follows: Firstly, China's natural resource utilization rate is relatively low, while the cost of resources is still relatively high; Secondly, the economic growth requires many resources to develop industries, like the construction industry (Steel, Petrochemical), or like the manufacturing industry (Coal, Oil, Natural Gas), this process will also lead to an energy crisis (Alimsyah and Faturohman, 2022). Thirdly, China's level of technology is relatively limited, and therefore the efficiency of industrial energy production is limited. On the other hand, the development of industrialization worldwide is now uneven. Developed countries have the most advanced technology in the world and are transferring traditional jobs to developing countries to produce. This transfer can increase the economic benefits of developing countries, but also environmental losses even though economic globalization has more advantages than disadvantages, therefore green behavior and consumption would be more important to us nowadays (Wardhana, 2022).

Over the past few years, the idea of "sustainable development" has been created to protect the land, and one of the most direct manifestations of this idea is carbon decoupling (DE). It means "severing the link between the economy and environmental issues", satisfying the need for sustainable development. The idea of DE emerged because the air that people save for survival contains high level of CO2 emissions, and this phenomenon, not only brings global warming problems to humankind, but hampers economic growth. According to Figure 1, from the perspective of GDP, we can calculate that China's GDP holds about 14% of the world's, which is not low compared to other countries. In terms of CE, China received 27% of the world score, which is higher than other countries. This demonstrates that China also has a responsibility to adjust carbon decoupling and better promote global sustainability. By the way, industrialization is the main power of EG, figuring out the influence of it on the decoupling could not only receive support for other sectors but get a convincing strategy for China to act. The development path of industrialization is transformed into a green state, making the process of decoupling from sustainable development more efficient.

So, the purposes of the study are as follows:

1) To find the decoupling status of China’s carbon emissions and economic growth and better adjust the decoupling state of the economy more efficient.
2) To learn the impact of industrialization and economic growth on the decoupling of China to better practice the sustainable development state.

2. LITERATURE REVIEW

Nowadays, the world is committed to building environmental protection and economic development to further promote sustainable development. The main reason for this engagement is that the negative impacts of GHG emissions are becoming increasingly apparent. The major sources of carbon emissions are like: transportation, urbanization, fossil fuel utilization, industry and construction (Khan et al.,2021). Among them, emissions linked to industry are the most important, and they have already threatened the development of human society. Therefore, there is a lot of research focused on industrial aspects and gradually turned into decoupling of CE and EG. This paper mainly depends

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on the economic theory, sustainable development theory, decoupling theory, EKC, and 3E system, so the related literature reviews will also follow a similar way (Ma et al., 2022).

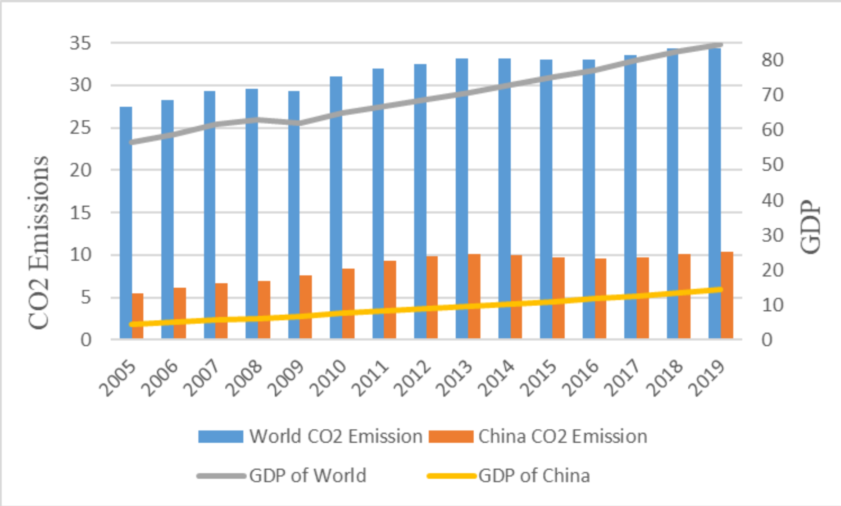

Figure.1 GDP of world & China and CO2 emissions of world & China
Source: World Bank & China National Statistical Yearbook

2.1 Decoupling Perspective

A series of recent studies have indicated that many researchers have focused on the state of DE carbon, particularly between the CE and EG. Much debate in the field of decoupling, (Du et al., 2022) studied the decoupling effect of CE from the industrial sector in China, and there is a trend of weak decoupling to strong decoupling for industrialization. They suggested that the government should make it compulsory to use energy intensively. Some have focused on relationships, like (Zhang, 2022) using panel data through the Tapio DE and LMDI index to show the DE situation between CE and EG. They noted that environmental impacts have been separated from economic growth and that energy intensity is important. That is the purpose of EG in the concept of sustainable development and the crucial existence of DE.And other objectives for DE, like (Wang et al., 2021) studied the influence of renewable power on CE in 25 countries following the Belt and Road from 2005-2019, showing that renewable energy could force decoupling. There are also studies on DE in a different direction, like (Jiang, Zhou, and Li, 2018) identified the DE in China from a sectoral perspective, and then found that the industrial sector creates more CE; they also proposed that technological innovation should be developed. Many scholars have also conducted multi-level studies on decoupling from other perspectives. (Rehman et al., 2021) argued the dynamic impact of carbon dioxide on economic progress is examined, and new concepts are proposed for implementing sustainable development paths. (Papież, Śmiech and Frodyma, 2021) suggests that energy policy can only be more efficient if it is shaped by the EU's carbon decoupling study into an operating model. From the OECD perspective, (Chen et al., 2018) showed that energy intensity reduces CO2 emissions, whereas GDP per capita is reversed and that technology is a key factor in the promotion of decoupling.

2.2 Industrial Sector Perspective

In the field of decoupling, the selection of research subjects is relatively complete. Many scholars have conducted considerable studies on industrial carbon sources, and the

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content has been extended to various industrial sectors. (Liu et al., 2021) studied the transportation sector, suggesting the need to actively encourage and support new technologies inside, while coal and crude oil need to be separately used. While (Chi et al., 2021; Li and Jiang, 2017) studied the construction sector, they developed a panel data decoupling model and argued that energy efficiency can contribute to carbon neutrality. Scholars (Jiang, Su, and Li, 2018) figured the relationship between CE and electricity output and find that the electricity sector is gradually becoming significant in CO2 emissions, and if we want to fix it, improving energy efficiency is the best way. Even in the tourism sector, (Deng, Zhou, and Xu, 2022) found that the DE relationship between tourism EG and CE in China is controlled by expansive linkages and suggested a focus on innovation and technological approaches. (Sui and Lv, 2021) have also studied the agricultural sector from several perspectives. In their study, they pointed out that only a few nations in the world achieved a strong DE in agriculture. These current conditions indicated that the progress of energy-efficient machines is an important trend. (Xia et al., 2020) argued that there is also a need for industry-specific research, they also studied the factors of industrial air pollutants, found that the main factors of pollution are altered by scale effect of population. In summary, most of the research models on decoupling are rooted in the Tapio DE model and LMDI analysis method, mainly from the consideration of consistency in the research perspective. However, other approaches have also been used: (Schröder and Storm, 2020) found that high-income levels may be forcing forces by regressing fixed effects on 58 countries within 2007-2015 using carbon framework. (Li, Niu, and Song, 2022) more based on the ARDL model, emphasizing that low-carbon construction is quite important, and developed countries the decoupling state is strong, while in developing countries the state is weak.

2.3 Research Gap

Based on the current development pattern in China, the practice of decoupling still has a long way to go. Current research on carbon decoupling is primarily restricted to the internal relationship of decoupling, and there is little research on influencing factors. As a result, there are several gaps in the existing literature that can be identified from previous studies. Firstly, among the existing literature on carbon decoupling, there are numerous studies on the direct connection between the CE and EG, but few academics have studied the effects. Secondly, most of the Chinese studies concluded more on the interaction between CE and EG. Moreover, few studies have divided all Chinese provinces into three major regions based on their level of EG. Regional division would be more useful for analysis. Finally, it may be observed that many carbon DE indicators in the literature are inseparable from the Tapio DE model and the LMDI model, but few studies use the panel-ARDL model. Particularly for each 30 provinces of objectives and combine them with the decoupling model to predict the long-term state of sustainable development. However, the panel-ARDL model is a more acceptable economic model of the factors which influence carbon decoupling.

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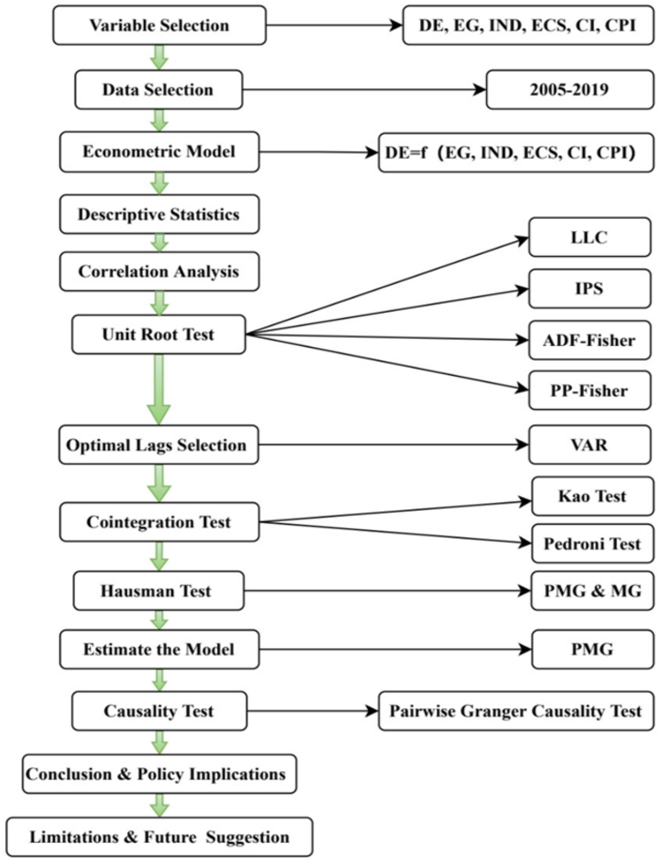
Fig. 2 Flowchart of the empirical analysis methods for the next study



3. DATA AND METHODOLOGY

3.1 Data Sources

The database of the research is collected from the China National Statistical Yearbook and Carbon Emissions Accounts & Datasets (CEADS) from 2005 to 2019. To be specific, the real GDP (2005 price index), CPI, coal energy consumption, total final energy consumption come from China National Statistical Yearbook, and carbon emissions come from CEADS. Among the models selected, the GDP growth rate represents economic growth (EG), and the ratio from $\Delta CO2\%$ to $\Delta GDP\%$ is symbolized by the decoupling elasticity (DE). Industrialization (IND) is represented by industrial added value and energy consumption structure (ECS) is the ratio between coal and total fuel. Carbon intensity (CI) is the proportion of CO2 emissions to GDP and CPI is the consumer price index of social welfare (CPI). (Table 1)

Table 1 Summary of Variables

	Variables	Definition	Unit
Dependent Variable	Decoupling Elasticity (DE)	Ratio of $\Delta CO2\%$ to $\Delta GDP\%$	%
Economy Sector	Economic Growth (EG)	Ratio of $\Delta GDP\%$	%
Economy Sector	Industrialization (IND)	Ratio of industry to GDP	%
Environment Sector	Energy Consumption Structure (ECS)	Ratio of coal to total fuel	%
Environment Sector	Carbon Intensity (CI)	Ratio of CO2 to GDP	%

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Social Sector	Consumer Price Index (CPI)	Index	%
Represent Sustainable Development 3 mainly sectors: Economy, Environment, Social			

3.2 The Model of Calculating CO2 Emission

According to CEADs' estimation methods, CO2 Emissions were constructed for 47 economic sectors and 17 types of fossil fuel (FF): (Figure 3 depicts the major fuels). Based on IPCC guidelines and CEADs methods, the equation of carbon emission is followed:

$$CEi = ADi * NCVi * CCi * O \tag{1}$$

Among the equation, CEi refers to the CE of FFi, there are 26 FFs but ignore small amounts so only combined them into 17. ADi is the "activity data", which is a series of FFi burned. $NCVi$ equal to "net calorific value", which is the heat worth produced by FF i. CCi is the "CE content" of FF i, which quantifies the CE one net calorific worth created. And O is the "oxidation efficiency", which shows the oxidation rate of the FF when burned (Guan et al., 2021).

Figure 3 shows that coal is the most consumed FF in China, followed by coke, diesel oil, and gasoline. As the most reliable source of energy for China's economic development and a major driver of industrialization, coal has also become an important element of the CE. Secondly, China's industrialization relative to GDP and GDP growth rate is roughly similar, indicating that industrialization has a close link to the Chinese economy. It is clear that industrialization also plays a central role in the development of China. Therefore, in terms of sustainable development, China needs to reduce environmental pollution as much as possible while developing its innovative economy and improving its efficiency.

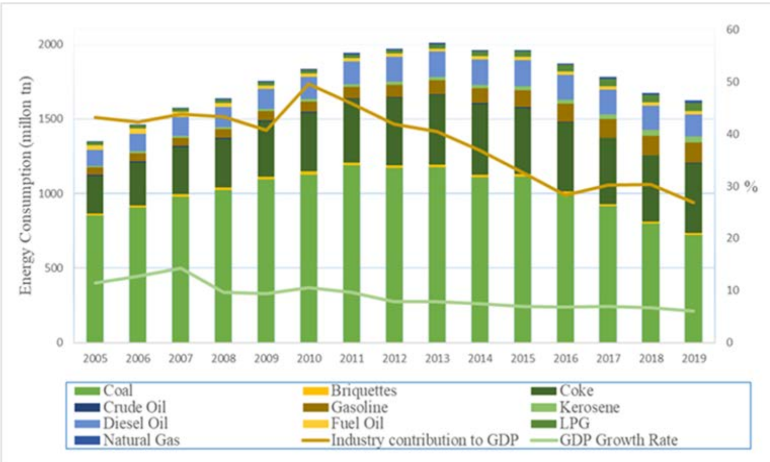

Figure.3 The mainly fuel consumption with industry rate and GDP growth rate in China
Source: China National Statistical Yearbook

3.3 Tapio Decoupling Model

This shows whether the variables are continuous with the change, and the Tapio DE model has been widely used to measure the link between EG and CE. The advantage of this model is that it offers choices about the base year, so it is more effective than the OECD model. Within this content, the DE index can be measured as below:

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$$DE = \frac{\Delta CO_2/CO_2}{\Delta GDP/GDP} = \frac{(CO_{2t}-CO_{2t-1}/CO_{2t-1}}{(GDP_t-GDP_{t-1}/GDP_{t-1}} \quad (2)$$

In the equation, DE is the decoupling elasticity, △CO2 is the scale of ΔCO2%, and △GDP is the scale of ΔGDP%. CO2 is the CE in the current year, and △CO2 is the change of CE in the current year fairly with the last phase; GDP is the gross domestic product in the present year, and △GDP is the change of GDP in the current year compared with the last time. The introduction of GDP and CO2 is mentioned in the data sources. As shown in the Figure 4 below, the total class of DE is divided into eight logical potions.

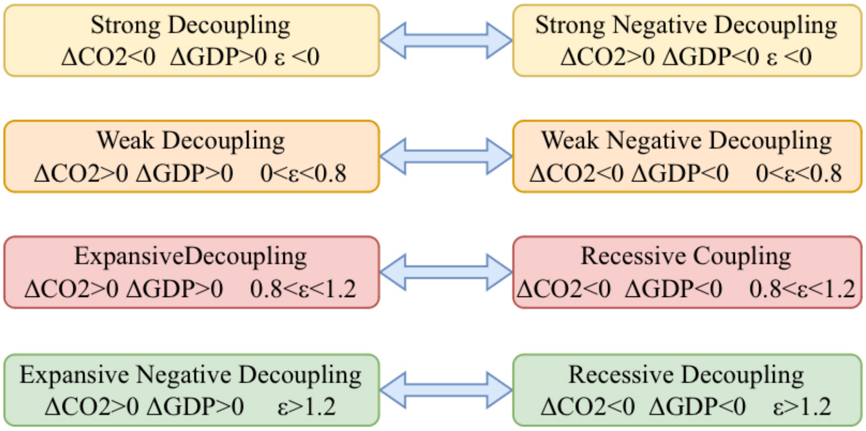

Figure. 4 The concept of decoupling states

3.4 Panel-ARDL Model

3.4.1 Panel-ARDL Model Construction

Based on the selected variables, the panel autoregressive distributed lag model (ARDL) approach (Pesaran, 1998) is chosen for this paper. The reasons for adopting the panel-ARDL are as follows. Firstly, the ARDL model leads to long-run relationships between variables, and these variables are not single instances of the same order. Secondly, compared with general linear regression models, panel ARDL helps to overcome the problem of endogenous variables. Finally, the ARDL model does not limit sample size and fully utilizes lags to represent relationships between variables.

Therefore, the following research equations are developed separately for the research method here:

- The basic relationship can be as followed:

$$\text{DE}=f\ (\text{EG, IND, ECS, CI, CPI}) \quad (3)$$

- Shifting to the linear model like:

$$\text{DE} = \beta 0 + \beta 1\ EG(t) + \beta 2\ IND(t) + \beta 3\ ECS(t) + \beta 4\ CI(t) + \beta 5\ CPI(t) + \varepsilon_t \quad (4)$$

In this equation, β0, …, β5 is the coefficients and ε_t is error term. And the DE is Decoupling Elasticity, EG is Economic Growth, IND is Industrialization, ECS is Energy Consumption Structure, CI is Carbon Intensity and CPI is Consumer Price Index.

- The short-term state of generalized panel-ARDL model

$$\text{ARDL (m, n, n…, n)}: y_{it} = \sum_{k=1}^{m} \varphi_{ik}\, y_{i,t-k} + \sum_{k=0}^{n} \phi'_{ik} X_{i,t-k} + \omega_i + \varepsilon_{it} \quad (5)$$

- The long-term state of generalized panel-ARDL model

$$\text{ARDL (m, n, n,…,n)}: y_{it} = \sum_{k=1}^{m} \varphi_{ik}\, y_{i,t-k} + \sum_{k=0}^{n} \phi'_{ik} X_{i,t-k} + \theta_i \left[y_{i,t-1} + X_{i,t-1}\right] + \omega_i + \varepsilon_{it} \quad (6)$$

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Where y_{it} is the dependent variable, $(X'_{it})'$ is a (k+1) dependent variables for group i, I (0), I (1) or mix. φ_{ik} is coefficient of lagged dependent variables (scalers). ϕ_{ik} is (k+1) coefficient vectors. ε_{it} is the error term and ω_i is unit-specific fix effect. θ_i is the long run coefficient. So, if both equations are derived from all variables, then they like:

- Short-term estimating equation

$$\Delta lnDE_t = \beta 0 + \sum_{k=1}^{m} \varphi_i \Delta lnDE_{t-k} + \sum_{k=0}^{n} \alpha_i \Delta lnEG_{t-k} + \sum_{k=0}^{n} \beta_i \Delta lnIND_{t-k} + \sum_{k=0}^{n} \gamma_i \Delta lnECS_{t-k} + \sum_{k=0}^{n} \delta_i \Delta lnCI_{t-k} + \sum_{k=0}^{n} \pi_i \Delta lnCPI_{t-k} + \omega_i + \varepsilon_{it} \quad (7)$$

- Long-term estimating equations (also stands for sustainable term)

$$\Delta lnDE_t = \beta 0 + \sum_{k=1}^{m} \varphi_i \Delta lnDE_{t-k} + \sum_{k=0}^{n} \alpha_i \Delta lnEG_{t-k} + \sum_{k=0}^{n} \beta_i \Delta lnIND_{t-k} + \sum_{k=0}^{n} \gamma_i \Delta lnECS_{t-k} + \sum_{k=0}^{n} \delta_i \Delta lnCI_{t-k} + \sum_{k=0}^{n} \pi_i \Delta lnCPI_{t-k} + \theta_1 lnDE_{t-1} + \theta_2 lnEG_{t-1} + \theta_3 lnIND_{t-1} + \theta_4 lnECS_{t-1} + \theta_5 lnCI_{t-1} + \theta_6 lnCPI_{t-1} + \omega_i + \varepsilon_{it} \quad (8)$$

In the above equation, $\varphi_i, \alpha_i, \beta_i, \gamma_i, \delta_i, \pi_i, \theta_i$ are also the coefficients, ε_{it} is the error term, and ω_i is a unit-specific fixed effect. And all variables are illustrated in equation (4). These functions solved the 2 purposes of my paper: (a) Figuring out the influence of the dependent variables IND, EG, ECS, CI and CPI on the independent variable DE; (b)Long-term relation of each variable to sustainability.

3.4.2 Panel Unit Root Test

Stationary analysis of the data set is a prerequisite for econometric analysis, in particular for macroeconomic data. Because the problem of spurious regressions may occur if the variables are not stationary. So it is important to check the serial stationary before using co-integration methods. There are 2 types for unit root test categories: type 1 is "not available for unbalanced panel data", like the Lavin-Lin-Chu test (LLC); And type 2 is "available for unbalanced panel data", like Augmented Dickey-Fuller test (ADF-fisher), and Phillips & Perron test (PP-fisher). We combine the three tests to conduct a stationary analysis, which could help us to compare the results.

- The basic function for the illustration of unit root test

Without Constant and Trend: $\Delta Y_t = \beta Y_{t-1} + \mu_t$ (9)

With Constant: $\Delta Y_t = \alpha + \beta Y_{t-1} + \mu_t$ (10)

With Constant and Trend: $\Delta Y_t = \alpha + \beta Y_{t-1} + \gamma T + \mu_t$ (11)

In this equation,Y_t is time series and α, β and γ are the modulus of the variables and μt is the error term. Based on the following hypothesis test and if the P-value < 0.1, 0.05, 0.1, it corresponds to reject the original hypothesis.

$H0{:}\ \beta = 0$ (non-stationary) $H1{:}\ \beta \neq 0$ (stationary)

And after the unit root test if the time series is not stationary at I (0) but at I (1) or I (2), then we need to do a co-integration test.

3.5 Panel Co-integration test

Pedroni (1999) (P) offered several panel co-integration test statistics that are based on the residue test. Kao (1999) (K) has the same test as before, proposing the H0: No co-integration relationship. However, contrary to P's claim, K assumes that the vector co-integration relationships will be considered homogeneous by individuals. Given the various test situations, we used both to verify this article. If the corrected p-value, reject H0, it means that there is a long way bind within the variables. Based on the basic equation of the generalized ARDL-panel model, if all variables are compatible with sustainable development theory, it could be:

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$$\Delta lnDEt = \beta 0 + \sum_{k=1}^{m} \varphi_i \Delta lnDE_{t-k} + \sum_{k=0}^{n} \alpha_i \Delta lnEG_{t-k} + \sum_{k=0}^{n} \beta_i \Delta lnIND_{t-k} + \sum_{k=0}^{n} \gamma_i \Delta lnECS_{t-k} + \sum_{k=0}^{n} \delta_i \Delta lnCI_{t-k} + \sum_{k=0}^{n} \pi_i \Delta lnCPI_{t-k} + £ECT_{t-1} + \omega_i + \varepsilon_{it} \quad (12)$$

Equation 12 £ is the representation of the error correction term and represents the long-way astringent adjustment rate of the determinant.

3.6 Hausman Test and Model Estimation

The Hausman test (H) is mainly contrasting the Mean Group (MG) and the Pooled Mean Group (PMG) estimator. According to the hypothesis, we could obtain a result about which estimator is more suitable for the variables. So, if the p-value < 0.05, then we could reject the H0, and choose the MG estimator, vice versa.

H0: Choosing to PMG   Ha: Choosing to MG

There is some difference between MG and PMG. If the parameters are homogeneous, PMG is more efficient because it contains the same long-term coefficients and enables the coefficients to differ between groups. But the MG estimator is invalid. And the basic assumptions of the PMG estimator are: First, its ε_{it} are not correlated as if they were exogenous. Second, all variables are related over time. Third, the same effects across groups (homogeneous). Thus, based on the H-test result and the estimate from the appropriate estimator, we could easily conclude the results. (The equation estimation is already shown in equation 2 to equation 8).

4. EMPIRICAL RESULTS

4.1 Decoupling analysis

Table 2 mainly reflects the summary of carbon decoupling coefficients for 30 Chinese provinces for regional aspects (east, central and west) in 2005-2009, 2009-2014 and 2015-2019, respectively. First, in general, the DE of 30 Chinese provinces in the table has five results: weak DE, strong DE, strong negative DE, expensive DE, and expansive negative DE. Among them, weak DE are the most, which indicates that China's carbon decoupling is still relatively optimistic. The expansive DE, strong DE, and strong negative DE are similar in amounts, but not account for a large proportion.

Secondly, from 2005-2009 to 2015-2019, only Yunnan has an expansive decoupling, Beijing and Shanghai demonstrate strong decoupling. However, Liaoning and Zhejiang show a strong negative DE. From a sustainability perspective, to better develop the economy without destroying the environment, China should strengthen its ability to impose strong decoupling.

Finally, strong decoupling occurs more in the central region than in the eastern region. The western region has the highest occurrence of expensive DE and strong decoupling between the three regions. Among them, Sichuan, Yunnan, and Chongqing have achieved strong decoupling in the period 2015-2019. As a result, Yunnan is still trying to save energy over the past 15 years.

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Table 2 Decoupling Elasticity of 30 Provinces of China

Years		2005-2009		2010-2014		2015-2019	
Regions	**Provinces**	**DE**	**States**	**DE**	**States**	**DE**	**States**
Eastern Provinces	Beijing	0.17	WD	-0.11	SD	-0.09	SD
	Tianjin	0.55	WD	0.41	WD	0.02	WD
	Hebei	0.61	WD	0.64	WD	0.46	WD
	Liaoning	0.70	WD	0.48	WD	0.24	SND
	Shanghai	0.27	WD	0.18	WD	-0.01	SD
	Jiangsu	0.59	WD	0.49	WD	0.30	WD
	Zhejiang	0.63	WD	0.19	WD	0.02	SND
	Fujian	0.81	ED	0.40	WD	0.22	WD
	Shandong	0.76	WD	0.25	WD	0.41	WD
	Guangdong	0.50	WD	0.29	WD	0.22	WD
	Hainan	0.64	WD	0.53	WD	0.13	WD
Central Provinces	Shanxi	0.45	WD	0.52	WD	0.37	WD
	Inner Mongolia	0.86	ED	0.59	WD	0.81	ED
	Jilin	0.63	WD	0.31	WD	-0.53	SD
	Heilongjiang	0.65	WD	0.60	WD	0.08	WD
	Anhui	0.64	WD	0.49	WD	0.23	WD
	Jiangxi	0.56	WD	0.52	WD	0.33	WD
	Henan	0.58	WD	0.34	WD	-0.36	SD
	Hubei	0.46	WD	0.24	SND	0.37	WD
	Hunan	0.80	ED	0.22	WD	0.25	WD
	Guangxi	0.72	WD	0.51	WD	0.34	WD
Western Provinces	Sichuan	0.49	WD	0.40	WD	-0.20	SD
	Guizhou	0.42	WD	0.26	WD	0.18	WD
	Yunnan	2.03	END	0.09	WD	-0.10	SD
	Chongqing	0.86	ED	0.27	WD	-0.08	SD
	Shaanxi	0.56	WD	0.54	WD	0.10	WD
	Gansu	0.37	WD	0.71	WD	0.01	WD
	Qinghai	0.74	WD	0.56	WD	0.14	WD
	Ningxia	0.25	WD	0.94	ED	0.98	ED
	Xinjiang	0.81	ED	0.96	ED	0.80	ED

SD=Strong Decoupling; SND=Strong Negative Decoupling; WD=Weak Decoupling ED=Expansive Decoupling; END=Expansive Negative Decoupling

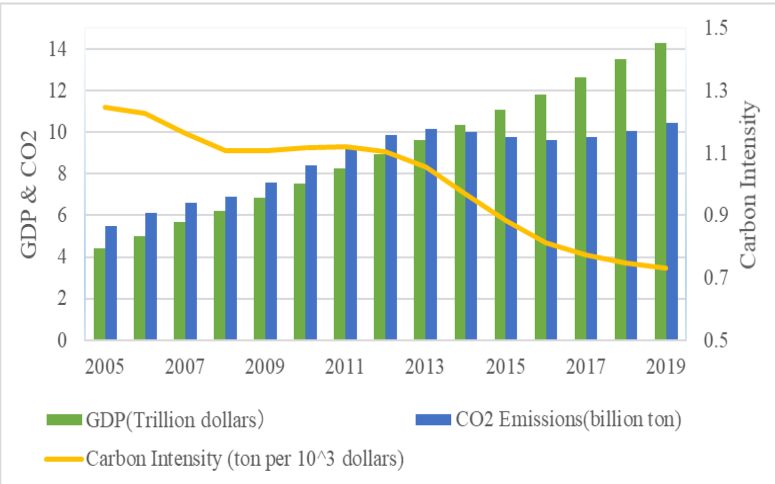

Figure. 9 The carbon intensity of China from the rate of GDP and CO2 emissions
Source: World Bank & CEADs

Carbon intensity is the percentage between CE and EG. According to Figure 9, China's GDP grew steadily from 2005 to 2019, and CO2 emissions continued to grow from 2005-2013 and achieved a fluctuating decline for next 5 years. It explains why carbon decoupling in Table 2 even appears strong decoupling in the period 2015-2019.

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4.2 Empirical Testing Results

Table 3 Descriptive Statistics

Variable	Obs	Mean	SD	Min	Median	Max	Kurtosis	Skewness
DE	450	0.382	0.3	-1.3	0.397	2.01	1.018	0.019
EG	450	0.13	0.004	-0.04	0.12	0.3	-0.516	0.278
IND	450	0.362	0.007	0.11	0.37	0.57	0.601	-0.505
ECS	450	0.751	0.014	0.35	0.77	0.94	0.496	-0.783
CI	450	0.075	0.002	0.01	0.06	0.24	1.319	1.273
CPI	450	102.643	3.041	97.7	102.3	108.2	0.519	0.553

From Table 3, we get a total of 2700 observations. As the data used in this paper have been converted to percentages, they are not taken in log format.

Table 4 Correlation Analysis

Variable	DE	EG	IND	ECS	CI	CPI
DE	1					
EG	0.121**	1				
IND	0.082*	0.240***	1			
ECS	0.083*	0.150***	0.405***	1		
CI	0.185***	0.176***	0.203***	0.518***	1	
CPI	-0.015	0.585***	0.116**	0.026	0.107**	1

Note: ***, **, * represent the significance levels of 1%, 5%, and 10% respectively

Table 4 shows that elasticity decoupling has a significant active effect on EG, IND, ECS and CI, while it has a negative impact on the CPI.

Table 5 Regression Analysis Result n=450

	B	SD	Beta	t	P	VIF	R^2	Adj. R^2	F
_cons	9.023	3.845	-	2.347	0.019**	-	0.06	0.046	F=5.306 P=0.000***
EG	3.189	1.13	0.165	2.821	0.005***	1.612			
IND	0.58	0.72	0.041	0.806	0.421	1.247			
ECS	-0.47	0.505	-0.05	-0.94	0.35	1.581			
CI	4.681	1.335	0.191	3.507	0.000***	1.391			
CPI	-0.09	0.038	-0.14	-2.38	0.018**	1.533			

Dependent variable: DE

Note: ***, **, * represent the significance levels of 1%, 5%, and 10% respectively

According to Table 5, we can verify that the values F=5.306 and P-value=0.000***, which reject the null hypothesis. And because the VIF < 10, therefore the model without multiple co-linearity. The link to the model is: y = 9.023 + 3.189*EG + 0.58*IND - 0.472*ECS + 4.681*CI - 0.09*CPI.

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Table 6 Panel data unit toot test results with trend

Variable	Method	At level		At 1st difference	
		t-statistic	Prob.	t-statistic	Prob.
DE	LLC	-3.221***	0.000	-10.182***	0.000
	ADF	5.623***	0.000	23.755***	0.000
	PP-Fisher	32.425***	0.000	63.891***	0.000
EG	LLC	-6.555***	0.000	-8.957***	0.000
	ADF	4.751***	0.000	15.254***	0.000
	PP-Fisher	11.940***	0.000	40.162***	0.000
IND	LLC	-4.787***	0.000	-6.697***	0.000
	ADF	-0.609	0.729	5.086***	0.000
	PP-Fisher	1.502	0.067	20.889***	0.000
ECS	LLC	-4.161***	0.000	-8.181***	0.000
	ADF	1.005	0.157	8.620***	0.000
	PP-Fisher	5.049***	0.000	26.661***	0.000
CI	LLC	-7.370***	0.000	-12.729***	0.000
	ADF	5.898***	0.000	21.300***	0.000
	PP-Fisher	10.691***	0.000	50.759***	0.000
CPI	LLC	-10.055***	0.000	-14.491***	0.000
	ADF	13.283***	0.000	28.651***	0.000
	PP-Fisher	20.506***	0.000	53.286***	0.000

Note: ***, **, * represent the significance levels of 1%, 5%, and 10% respectively

Table 6 is a tool used to analyze a time series is stationary or not, and having it means non-stationary. The significance of the unit root test is determined by the P-value, and the H0: panels contain a unit root. So, if the $P < 0.05$ then we could reject the H0, which indicates stationary. According to Table 6, after the first-order difference, the significant P for all variables is $P=0<0.05$, so that H0 is rejected. Then the sequence is stationary.

Table 7 Optimal lags selection

Lags order	Log L	AIC	SC	HQ	FPE
0	679.15	-20.019	-19.964	-19.997	0
1	1957.96	-25.562	-25.177*	-25.41	0
2	2041.2	-25.792*	-25.077	-25.51*	0
3	2093.25	-25.883	-24.837	-25.47	0

Table 7 is the autoregressive vector model (VAR) which can analyze the optimum lag order of the time series. The results of FPE, AIC, SC, and HQ show that lag order 2 has the most *, so L(2) is chosen as the optimal lag choice. From Table 8, the criterion for the co-integration test is whether $p < 0.05$, if it is below zero, then we may reject H0: No co-integration. As a result, we can conclude that there is a long-term link in all the variables. Table 9 indicates Prob=0.9919>0.05, therefore the null hypothesis is accepted, which

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means that the PMG estimator will be used. Table 8 concludes that there is a long-term link between all the variables, then table 10 will also focus on the long-run.It shows that the EG, IND and CI have a gradual effect on ED, while ECS and CPI have a reverse effect.

Table 8 Result of co-integration test

Test	M(DF)=Modified (Dickey–Fuller) ADF= Augmented Dickey–Fuller PP= Phillips–Perron		t-Statistic	p-value
Kao test	Without trend	MDF t	-6.2665	0.0000
		DF t	-10.938	0.0000
		ADF t	6.7044	0.0000
Pedroni test	Without trend	MDF t	6.752	0.0000
		PP t	-16.3904	0.0000
		ADF t	-8.0884	0.0000
Pedroni test	With trend	MDF t	7.983	0.0000
		PP t	-22.2316	0.0000
		ADF t	-9.5832	0.0000

Note: ***, **, * represent the significance levels of 1%, 5%, and 10% respectively

Table 9 Hausman test

Hypothesis: H0: PMG; Ha: MG

Variables	MG	PMG	Difference	S.E.
EG	-2.63106	2.565856	-5.196915	43.40758
IND	1.675932	1.541086	0.1348458	45.30137
ECS	-11.4749	-0.94922	-10.5257	62.70523
CI	-24.3497	2.337018	-26.68672	77.65659
CPI	-0.26652	-0.08626	-0.1802554	1.216475

The result: prob=0.9919 > 0.05

Reject the null hypothesis is the p-value<0.05

Table 10 Estimate the PMG - ARDL Model

	Variables	Coefficient	Std. Err.	z	P>|z|
Long Run	EG	2.566	0.608	4.220	0.000
	IND	1.541	0.549	2.810	0.005
	ECS	-0.949	0.202	-4.700	0.000
	CI	2.337	1.355	1.730	0.084
	CPI	-0.086	0.020	-4.410	0.000
Short Run	ECT	-1.037	0.051	-20.420	0.000
	EG_D1.	0.563	1.471	0.380	0.702
	IND_D1.	1.718	3.996	0.430	0.667
	ECS_D1.	1.658	2.762	0.600	0.548
	CI_D1.	22.240	5.873	3.790	0.000
	CPI_D1.	-0.019	0.032	-0.590	0.558
	_Cons	9.319	0.445	20.950	0.000

Mainly focus on the long run results

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5. CONCLUSION AND POLICY IMPLICATIONS

Over the past 15 years, the issue of EG and environmental problem has become a major concern worldwide. There are the conclusions about the empirical results.

First, it is shown that economic growth, industrialization and carbon intensity facilitate the decoupling, while the energy consumption structure and the consumer price index revert. Of the positive impacts, economic growth (2.566) has the stunning effect of decoupling, followed by carbon intensity (2.337) and finally industrialization (1.541). In contrast, the energy consumption structure (-0.949) has the greatest impact, followed by the consumer price index (-0.086). Second, according to the three broad areas of sustainable development, it has a positive impact on economic and environmental sustainability, while social sustainability needs to be improved. Meanwhile, China shows that most Chinese provinces are in a weak DE state, and there is still a long way to go. Finally, according to the CEADs, the largest carbon emissions are in eastern China. This depends on levels of economic development in China's three main areas.

Based on the main findings of this paper, there are three recommendations for effective decoupling in China. First, economically, we should reduce our dependence on fossil fuels and develop technologies to improve energy efficiency. China should actively encourage the conversion of energy, such as hydropower and power generation. And CO2 policies, like carbon taxes. Second, environmentally, the government can encourage people to participate in afforestation activities, such as sorting the waste for recycling. China should also develop a suitable policy for the different problems of the 30 provinces. For example, the government can invest more in eastern China to help it transform its technology to solve the pollution issue. Finally, socially, the public should improve their over-consumption habits such as cycling when driving is not required. Companies should comply with environmental laws and make efforts to get their companies to reach cleaner targets. The government should also monitor changes in the consumer market and make comprehensive adjustments in consumer attitudes.

6. LIMITATIONS AND FUTURE SUGGESTIONS

On the one hand, this article has limits too. First, the sample size of the panel data is not large enough. Secondly, there are limitations in the tools used for data analysis. Finally, this paper mainly of three major regions in China, ignoring the individual provinces.

On the other hand, it also provides well-founded ideas for future research in the areas of decoupling. Furthermore, it offers a future scope for sustainable development research from an economic, environmental, and societal perspective. This article also has a benchmark for future research that takes China as a research topic.

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